Comparison on flight delay propagation base on the mechanism of epidemic spreading

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ABSTRACT

This paper investigates flight delay propagation in air transportation networks (ATNs) by considering both network structures and airport operation performance. An airport susceptible-infected-recovered (ASIR) model is established based on the mechanism of epidemic spreading, where the effective infected rate is mainly discussed in order to map flight delay propagation properly. Different network configurations were abstracted under complex network theory, in which the ASIR model can be simulated upon. The simulation results show that airport traffic (especially for those where delays are originated), airport connection and the level of airport turnaround services play important roles in influencing delay propagation in different airports. In addition, changes of network structure such as the emerging of secondary hubs can also influence the delay propagation.

1. INTRODUCTION

The global aviation industry has experienced an unprecedented growth in terms of supply and demand. It is expected that by 2030, the total number of flights will double and the total number of passenger-kilometers flown will nearly triple (Airbus, 2012). This growth can be considered as desired from a development point of view, but will also have a number of important drawbacks. For one, it will induce a higher risk in flight delays, of which will lead to economic losses (Cook and Tanner, 2011; Takeichi et al., 2013), negative impact on the environment (Prats and Hansen, 2011) and will alter demand-determining factors (passengers and cargo). When flight

delays occur and spread over an entire network, implying that delays originating from an upstream flight infect downstream flights, this process is referred to as flight delay propagation (Kafle, N., Zou, 2016). Hence, any delay related to resources of upstream flights, such as late inbound aircraft, crew, and passengers can lead to delays to a departure flight, which will further impact its connected downstream flight (Wu and Wu, 2018). Moreover, there are also a number of other factors that will impact flight delay propagation such as: congestion at hub airports, unequal distribution of route traffic, emergence of secondary hub airports, and varied operation capabilities among airports (Asfe et al., 2014; Zámková and Prokop, 2015). Those factors are always network, spatial and time implicated.

A range of aspects has been investigated to deal with mechanisms of flight delay propagation. Several related factors such as aircraft, airline operations, change of procedures and traffic volume are discussed by Mueller and Chatterji (2016) when modeling airport departure and arrival delay time distribution. Baspinar et al. (2016) analyzed the impact of airport capacity on the total delay time and found that airports with capacity below a critical threshold can prolong the total delay time. Recently, researchers paid more attention on how route and airport-related attributes influence the delay propagation from a network perspective. For instance, Kondo (2009) found that delay propagation can be magnified in terms of number of delayed flights and total delay time if airports are strongly connected to each other. Pyrgiotis et al. (2013) showed that the delays propagated over hub airports may restrain demand given a network consisting of 34 busy airports in the United States.

Complex network theory has also been applied to model dynamics (e.g., epidemic spreading and delay propagation) in transportation networks (Zanin et al., 2018). The network growth, routing traffic and hub capacity etc. are found to have large impact on network structure and consequently will impact how behaviors propagate (Ducruet and Beauguitte, 2014; O'Kelly, 2015; Yang et al., 2012; Nakata and Röst, 2015). Furthermore, Baspinar and Koyuncu (2016) innovatively combined the SIR model with complex theory to examine the delay propagation in ATNs, follows its similarity with epidemic spreading. In particular, they paid attention on the mechanism of delay propagation in ATNs with scale-free characteristics that can be found in most of ATNs (Dong, 2014; Barabási and Albert, 1999). However, they considered neither the factors that can also influence the probability of delay propagation in ATNs when establishing the network nor did they take account of the changes of network structure (Sun et al., 2013).

At present, literatures above devoted in finding out the causes and characteristics of delay propagation in air transport network. Different methodology were used such as queuing theory, Bayesian network, and epidemic spreading model (i.e. SIR model etc.). Therefore, in this paper, the Airport susceptible-infected-recovered (ASIR) models is established based on Baspinar and Koyuncu (2016). Meanwhile, an abstract simulation environment for ATNs is generated by using complex network theory so as to study the impact of different network configurations on the propagation of delay. Improved from the previous literature, we redefines the probability of delay propagation from the perspective of network configuration such as airport connectivity (i.e. airport degree k) and airport operation (e.g. airport annual passenger flow, airport operation efficiency, etc.) to explore in what ways airport traffic, airport turnaround operations and network configures influence the flight delay propagation in different air transport networks as the ATNs structure changes. We contribute to the literature in terms of studying the characteristics of flight delay propagation based on epidemic spreading mechanisms and establish a relationship between delay propagation and network structures by considering both airport connection and the airport traffic. It has been shown that as the network developed, the scope of the delay propagation has changed.

Not only airports with larger traffic can easily generate delays but also the emerged regional/secondary airport becomes the main factors that effect the delay propagation. That is because the number of these airports is becoming larger but the resources (such as runway, terminals and etc.) are limited.

This paper is organized as follows. In Section 2, we first introduce how epidemic spreading mechanism were used in studying flight delay propagation and then the ASIR model were constructed based on SIR model. Factors impact to the probability of delay propagation (i.e. the infected rate) were also discussed. Section 3 presents three different ATNs which is an evolving process of Chinese air transport network from year 2007 to 2017. Complex network theory was used to abstract the real ATNs into simulation ones which is easier and clearer for further characteristics simulating of flight delay propagation. Section 4 presents the simulation results and discussion. Section 5 concludes and puts forwards some avenues for further research.

2. THE ASIR MODEL

This section introduces how to model delay propagation in ATNs by considering the impacts of network structure, airport traffic and turnaround operations. In particular, the methodology used to express the process of delay propagation is based on the conventional susceptible-infected-recovered (SIR) model which originally applied in the epidemic spreading discipline. Similar to Baspinar and Koyuncu (2016), flight delay propagation mechanism can be corresponded to some epidemic spreading such as smallpox which can no longer be infected again once recovered. That is because, from our examine time scales (always in one day time), airports always closed or curfew in the end of the operation day, there are no departure or arrival flights therefore, no delay can be propagated from these airports.

To be explicit, delay propagation progression in ATNs is described as follow. There are three types of airports in the network, and Fig. 1 depicts the origination and progression of delay propagation across airports. When delays occur in a 'susceptible' airport, airports connected to the susceptible airport may be 'infected' through flights and become delayed airports. As flights are scheduled subsequently from one route to another, delays can thus be propagated to other airports that are not directly connected to the original susceptible airports, i.e., along the entire network (Colizza et al., 2006). Following the measures taken to mitigate delays, the infected airports can be 'recovered'.

Figure 1. The progression of delay propagation across airports in a network.

This process is determined by two subsequent transition states - infected and recovered rates as denoted by β and μ respectively. β refers to the probability that a susceptible airport becomes a delayed airport; μ refers to the probability that a delayed airport becomes a recovered airport. As this paper examines the delay propagation pattern from a network-wide perspective, recovered rate only effects the time scale definition of spreading (Yang, 2012). Therefore, the recovery rate μ is set to be 1. In addition, in the application of real flight delay network, all infected airports are considered to be recovered at the end of the day, which indicate that network can returned to its original situation with no delayed airport in a limited time (often in one day), and what we focus on is how these delays propagate between airports in a day time.

2.1 Model Explanation

Based on the aforementioned process of delay propagation, we propose an airport susceptible-infected-recovered (ASIR) model as expressed by the following differential equations (Eq. 1).

$$\begin{cases} \dfrac{dI_k(t)}{dt} = -\mu I_K(t) + \beta k S_k(t)\Theta_k(t) \\ \dfrac{dS_k(t)}{dt} = -\beta k S(t)\Theta_k(t) \end{cases} \qquad (1)$$

Where:

(1) k refers to the degree of an airport in the network, which indicate the total number of its connected airports.

(2) t refers to time step, $t \in [1, T]$, where T is a value close to infinity to guarantee the model convergence.

(3) $S_k(t)$, $I_k(t)$ and $R_k(t)$ refer to the proportion of susceptible, infected, and recovered airports among airports with degree k at time t, respectively. The sum of these three parameters should be equal to 1, i.e. $S_k(t) + I_k(t) + R_k(t) = 1$.

(4) $\Theta_k(t)$ refers to the probability that an airport with degree k connects to a delayed airport at time t. As higher degree of airports does not mean larger probability connecting to a delayed airport in ATNs (Meloni et al., 2012), the value of $\Theta_k(t)$ is thus linearly influenced by the degree distribution of a network and the proportion of delayed airports with degree k at time t, as measured below (Eq. 2).

$$\Theta_k(t) = \sum_k kP(k)I_k(t)/< k > \qquad (2)$$

Where, $P(k)$ is the degree distribution of a network. $< k >$ is the average degree of a network and measured as $< k > = \sum_{k \in N} k * P(k)$, with N the total number of airports in a network.

(5) Equation in Eq. (1) refers to the changing rate that susceptible airports are transformed into infected airports, and the probability that infected airports changed back to susceptible airports respectively. Therefore, the effective infection rate can be rewrite as $\lambda = \beta/\mu$. In this paper, it is a function of airport category α which is influenced by both airport traffic and its turnaround efficiency q. We will detailly defined λ in section 2.1.2. In the basic SIR mode, the propagation of delays occurs only if the propagation probability is larger than a theoretically determined threshold λ_c measured as: $\lambda_c = < k > / < k^2 >$, it is also appropriate to ASIR model even modified by α and q.

2.2 Effective delay propagation probability

The effective delay propagation probability λ is the core of this model and can be influenced by several factors (Fan et al., 2014). We mainly consider three factors – network configuration, airport traffic and turnaround service level where delays are originated and explore in what ways these three factors influence the delay propagation. Therefore, λ is first measured as follows (Eq. 3).

$$\lambda(\alpha) = (S_\alpha/S_{max})^q \qquad (3)$$

Where, S_a refers to the annual traffic of airport α where the delays are originated, while S_{max} refers to the maximum traffic among all airports in the same network. q refers to the level of airport turnaround services and is set to be between 0 and 1.

The format design of Eq. 3 demonstrates the simplified non-linear relationship between the delay propagation probability $\lambda(\alpha)$, airport traffic S_a and turnaround service level q. In general, higher airport traffic may lead to more congestion therefore more delay flights; on contrary, higher level of airport turnaround operation performance may largely ensure on-time arrival and departure, especially for these connecting flights (Fan et al., 2014). As the algorithm presented by (Chunki Park et al., 2012) pointed out that the average per flight delay was reduced by 30% even when the transit times are only permitted to increase by 5%. It is reasonable to say that airport turnaround efficiency should be considered.

In our model, assuming that q is fixed, the larger number of airport traffic, the higher probability that delays can be propagated; assuming that annual airport traffic is fixed, the exponential function means that the higher the level of turnaround services, the lower probability that delays can be spreaded.

Furthermore, the impact of network structure is investigated by considering airport degree k into delay propagation probability. Even in the same airport category, airports with different degree may have different connectivity, hence may show different propagation ability. In this way, λ in Eq.3 can be measured as follows (Eq. 4).

$$\lambda_k(\alpha) = \left(\frac{S_k(\alpha)}{S_{max}}\right)^q \tag{4}$$

And the ASIR model can be rewritten as:

$$\begin{cases} \dfrac{dI_k(t)}{dt} = -I_K(t) + \lambda_k(\alpha)kS_k(t)\Theta_k(t) \\ \dfrac{dS_k(t)}{dt} = -\lambda_k(\alpha)kS(t)\Theta_k(t) \end{cases} \tag{5}$$

From the established ASIR model, flight delay propagation is not only related to airport traffic and turnaround service level, but also influenced by different network configurations. Based on the degree distribution, the proportion of all delayed and susceptible airports in the network at time t can be respectively obtained by the following equation: $I(t) = \sum_k I_k(t) * P(k)$ and $S(t) = \sum_k S_k(t) * P(k)$.

3. DEVELOPMENT OF ATNS

Different network structure and airport traffic will influence the delay propagation differently, it is necessary to investigate how network structure changes and airport emerge during time goes. Fig.2 shows a toy model of a hub-and-spoke network configuration changing

as the total number of airports increases. As can be seen, a more hierarchical network structure tends to emerge with a larger scale.

(a) N=20   (b) N=40   (c) N=80

(a) N=120   (b) N=150   (c) N=200
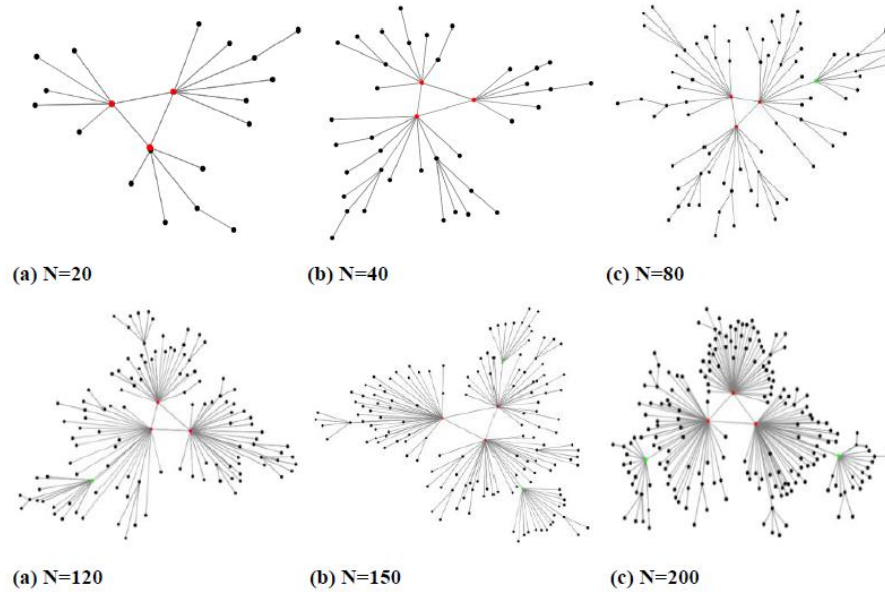
Figure 2. Simulation of network evolution.

As it takes a long time for the ATN structures changed, airports do not emerge dynamically in air transportation networks, but, instead, such networks are highly stable over time. Hence, in order to further explore the mechanism of the impact different network structures on the delay propagation, we examine three stages during China ATN development (i.e. 2007, 2012, 2017).

A specific category of each airports is presented based on the data collected from ACI (Airport Council International) classification, which is mainly classified by airport traffic share. In Table 1,S_a.refers to the airport traffic of airport and S_{max} refers to the maximum airport traffic of an individual airport in the network. After changing for decades, China's airport network tends to have more mulit-airport system and focus on the development of regional airports in recent years. Airports are more clustered and the number of different category airport has changed.

In this case, how delays spread among these three different networks is the significance research of this paper.

Table 1 Percentage of different types of airports under different network scales

| Airport category (Sa/Smax) year	A ≥0.5	B [0.2,0.5)	C [0.03,0.2)	D [0,0.003)
2007 (Network 1, N=149)	3	6	30	110
2012 (Network 2, N=183)	3	8	32	140
2017 (Network 3, N=229)	4	16	29	180

4. SIMULATION RESULTS

Drawing on the proposed ASIR model, this section investigates the impact of airport traffic, the level of airport turnaround services and network structures on the delay propagation. In particular, the impacts of airport traffic and airport turnaround services level are first investigated in a focused network configuration (i.e. Network3). Then how network structures influence delay propagation are examined in three different network scenarios. The proportion distribution of delayed and recovered airports are examined based on the four different categories (i.e., category A, B, C and D as defined in section 3), in order to reveal how these three factors influence the delay propagation in ATNs.

4.1 Factors Effect Delay Propagation

4.1.1 Airport Type Effect

Supposing that the turnaround services are at a high level with $q = 0.8$, we consider category B and C airports as the initial susceptible airports. Fig. 3 presents the proportion distribution of delayed airports under different airport types.
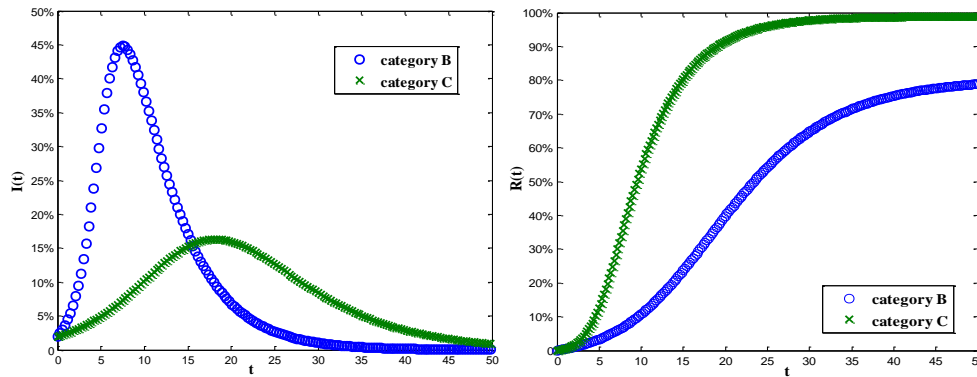

Figure 3. Airport traffic effect under different categories.

As can be seen, the maximum proportion of delayed airports for airport categories with larger traffic (i.e., category B) is much higher than that for the airports with less traffic (i.e., category C). The time to reach the maximum proportion for the former is shorter than that for the latter. This can be explained by the fact that the propagation probabilities of the former (0.87) are much larger than the theoretical threshold (0.39), while the propagation probabilities of their counterparts (0.40) are close to the threshold. As the delay can merely spread when the propagation probability is above its theoretical threshold, an effective way to control the spread of delays is to take measures to restrain delays at airports with larger traffic. For instance, priorities can be given, or longer buffer time can be scheduled for departure flights at these airports where delay propagation originally occurs with a higher probability.

4.1.2 Airport Turnaround Service Level

The probability of delay propagation depends on not only an airport's traffic and connection, but also its operation service level, for instance, the airport turnaround service level. Theoretically, the departure/arrival delay time can be reduced if the buffer time of aircraft turnaround is appropriately scheduled and airports can provide high level of turnaround services. As have proven in section 4.1.1, delays can be easily transmitted starting from airports with large volumes of traffic (e.g., category A and B airports). We, therefore, use category B airports to illustrate whether delay propagation can be controlled by improving the turnaround service level

at these airports. A high level of airport turnaround service is assumed to be between 0.5 and 1 in this paper. Fig. 6 shows the impact of the airport turnaround service level on the delay propagation by setting four linearly increased levels (i.e., 0.5, 0.6, 0.7, 0.8).
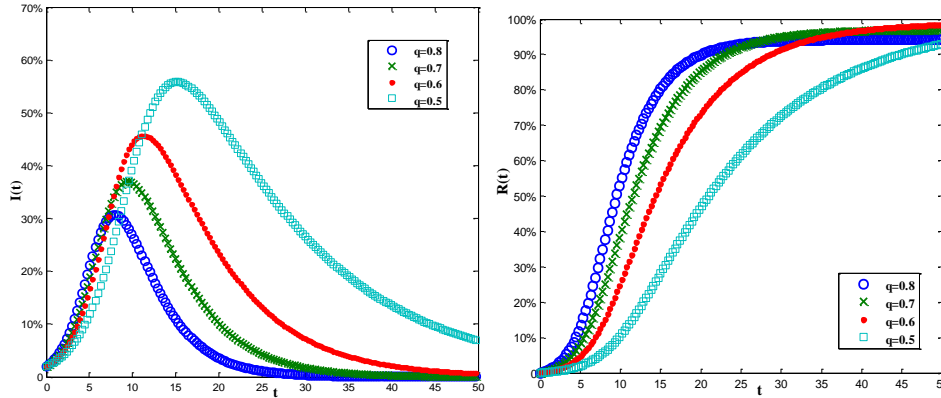
Figure 4. Airport turnaround service level effect.

As the level of the airport turnaround service gradually improves, the proportion of delayed airports decreases nearly in all the time moments and the total time for the delayed airports to diminish is also less. This finding corresponds to the result of the right figure where the speed of infected airports to recover is much faster at airports with higher level of turnaround services.

In fact, the improved turnaround services at airports together with the proper buffer time can not only guarantee the on-time departure/arrival of a flight, but also mitigate the temporary saturation of airports due to flight delays (Jacquillat and Odoni, 2015). Therefore, airports should strive to improve the level of the turnaround service level by taking effective airport control management, for instance, investing more human resources during peak hours, or applying automatic facilities in the key links of airport turnaround operation, which can help restraining the spread of delays in terms of the scale and speed.

4.2 Network Structure Effects

4.2.1 ASIR in Three Networks

We investigate the impact of the network structures on the delay propagation by examining how the proportion of the number of delayed airports $I(t)$ changes under different networks proposed in Fig. 4. Supposing the turnaround service is at a high level with $q = 0.8$, Fig. 5 shows that: (1) the maximum proportion of the number of delayed airports is reduced as network evolves into a hub-and-spoke structure; (2) the time reaching its maximum is also prolonged. This means different network structures can influence the pattern of delay propagation in terms of both scale and speed. During one decade's evolution, routes in China's network becomes more dense and the total passenger volume nearly triple increased. Compare to the high speed in traffic increment, the decline of on time performance (OTP) is slowed down. In fact, the decreasing rate of OTP in 2012 and 2017 is 5.71% and 4.98% respectively, which indicate only an average of 0.83% OTP decline in each year over the whole decade. Despite of the government investment for airport facilities construction supporting, easier connection between airports and the evolving of multi-airport system is also one of the main reasons to restrain delay propagation. This illustrates that carriers tend to adopt a multi-hub-and-spoke network structure in order to relieve the congestion and severe schedule delays at their primary hubs (Marta, 2011). Our findings prove that such a strategy can

effectively restrain the spread of delay by reducing the number of delayed airports and the delay time, especially in the condition of the significant increase of route traffic.
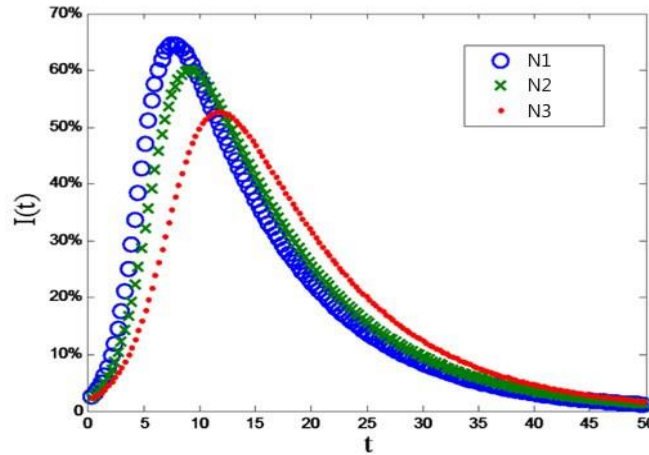
Figure 5. Route traffic effect on the delay propagation.

4.2.2 Combination Effect

We consider an integrated effect by designing four scenarios with the level of the airport turnaround service q = 0.5, 0.7 and 0.9 (i.e., representing low, medium and high level, respectively) as well as different network structures (i.e., N1 and N3, respectively) in Fig. 6. As it seems to be unrealistic for an airport to have high volumes of route traffic but lower level of turnaround services (i.e., a scenario of N3, p=0.5) or low volumes of route traffic but high level of turnaround services (i.e., a scenario of N1, p=0.9), we do not consider these two cases in our simulations.
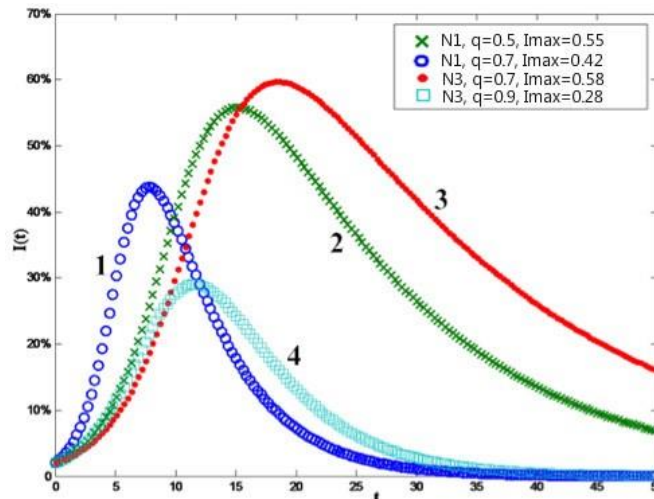
Figure 6. Integrated effects of airport turnaround level and route traffic.

Four distributions representing the aforementioned four scenarios are labeled as 1, 2, 3, and 4, respectively. Two comparisons (i.e., scenario 1 vs. 2 and scenario 3 vs. 4) show that higher level of airport turnaround services does effectively control the propagation of delays in all kinds of networks. This finding further confirms the simulation result of section 4.1.2.

When the level of airport turnaround services maintains at the medium level (scenario1 and 3), delay propagation in N1 and N3 lead to two different situations. At the initial time moment, the proportions of delayed airports for scenario 1 are higher than those of scenario 3. However, as time passed, it seems that delays caused by the network 1 can be gradually dissolved as long as the airports can provide at least medium level of turnaround services (curve 1). As more flights involved, the maximum proportions of delayed airports in N3 is nearly 1.5 more than that of N1. Consequently, the time that scenario 3 reaches to its peak is also nearly three times longer than that of scenario 1. This is due to the fact that the delays start severely spreading in this scenario with its propagation probability (0.87) being larger than the threshold.

In addition, as curve 4 is located almost under all the other three curves, it shows that the high level of airport turnaround services can significantly reduce the number of delayed airports and suppress the propagation of delays, even in the case of N3 with larger airports emerged and dense routes.

5. CONCLUSION

This paper investigated how airport traffic, turnaround operations and network structure influence the flight delay propagation as China's air transport networks evolves simultaneously.

We contribute to the literature in terms of studying the characteristics of flight delay propagation based on epidemic spreading mechanisms. Contrary to the examination of delay propagation in different networks configurations, we establish a relationship between delay propagation and network structures by considering both airport connection (i.e. airport degree) and the airport traffic. Then we reveal how factors such as airport traffic growth and the emerge of multi-airport system influence the flight delay propagation. The ASIR model allows to not only quantify the process of flight delay propagation by considering the scope and lasting time of propagation, but also incorporate factors influencing the delay propagation.

As the network appear to be a more typical hub-and-spoke structure, the scope of the delay propagation is narrowed and the spreading speed is slowed down. This is not only related to the network configuration itself, but also due to the evolution of secondary/regional hub airports which are in the role of sharing traffic effectively. It is, therefore, suggested that the saturation of primary hubs forces carriers to establish secondary hubs to accommodate the spillover traffic and may design their own the multi-hub-and-spoke network configuration to restrain the propagation of delays. Meanwhile, airlines adopting a medium-traffic expansion strategy should be encouraged to enter into small airports with larger traffic growth potential, meanwhile without suffering from the loss of delays.

In all these three network structures, airports with larger traffic can not only easily generate delays but also swiftly spread delays to a large proportion of airports. It is obviously that airports with larger traffic should be effectively controlled before the delay starts spreading from these airports. However, when the network structure evolved and more regional/secondary airport emerged, the main effects of delay propagation is gradually transferred from hub airports to these airports. That is because the number of secondary/regional airports is becoming larger but the resources (such as runway, terminals and etc.) there are not developed yet. Once it is congested, more time are needed to recover.

Therefore, despite attracting passengers and airlines, policy makers and local governments should support the development of these airports. The increase of route traffic should match the level of airport turnaround services in order to control the delay propagation in term of its scale and time. The ambitious expansion of route traffic should be guaranteed by a high level of airport turnaround services.

This paper has been done with limitations that can be improved for further research. First, empirical studies for real air transport networks (e.g., ATNs in China) should be provided to further validate the simulation results. Second, although we explore airport traffic and airport connection as the main factor that drives network change and delay propagation simultaneously, other factors, such as yield and distance, can also be included in the model in the future.

Acknowledgement

References

Airbus. (2012). "Global market forecast 2012-2031". *Available from www.airbus.com/company/market/forecast/ Accessed 20.08.13*.

Asfe, M.K., Zehi, M.J., Tash, M.N.S., Yaghoubi, N.M. (2014). "Ranking different factors influencing flight delay." *Management Science Letters*, 4(7), 1397-1400.

Barabási, A.L., Albert, R.（1999）. "Emergence of scaling in random networks." *Science*, 286, 509-512.

Baspinar, B., Koyuncu, E. (2016). "A Data-Driven Air Transportation Delay Propagation Model Using Epidemic Process Models." *International Journal of Aerospace Engineering*, 7, 1-11.

Baspinar, B., Ure, N.K., Koyuncu, E., Inalhan, G. (2016). "Analysis of Delay Characteristics of European Air Traffic through a Data-Driven Airport-Centric Queuing Network Model." *IFAC Papers OnLine*, 49(3), 359-364.

Chunki Park, Hak-tae Lee, Larry Meyn. (2012). "Computing Flight Departure Times Using an Advanced First-Come First-Served Scheduler." *12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference and 14th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference (AIAA). Aiaa Journal*, 1-8.

Colizza, V., Barrat, A., Barthélemy, M., Vespignani, A. (2006). "The role of the airline transportation network in the prediction and predictability of global epidemics." *Proceedings of the National Academy of Sciences of the United States of America*, 103(7), 2015-2020.Cook, A. J., and Tanner, G. (2011) "European airline delay cost reference values." *Eurocontrol Performance Review Unit*. London.

Dong, B. (2014). "Reliability Analysis for Aviation Airline Network Based on Complex Network." *Journal of Aerospace Technology & Management*, 6(2), 193-201.

Ducruet C., Beauguitte L. (2014). "Spatial Science and Network Science: Review and Outcomes of a Complex Relationship." *Networks & Spatial Economics*, 14(3-4), 297-316.

Fan, L.W., Wu, F., Zhou, P. (2013). "Efficiency measurement of Chinese airports with flight delays by directional distance function." *Journal of Air Transport Management*, 34(1), 140-145.

Jacquillat, A., Odoni, A.R. (2015). "An Integrated Scheduling and Operations Approach to Airport Congestion Mitigation." *Operations Research*, 63(6), 1390-1410.

Kafle, N., Zou, B.（2016）. "Modeling flight delay propagation: A new analytical-econometric approach." *Transportation Research Part B: Methodological*, 93, 520-542.

Kondo, A. (2009). "Delay Propagation and Multiplier." *Transportation Research Board Annual Meeting*, Washington.

Marta, S. (2011). "Dynamic Approaches from Complexity to Manage the Air Transport Network." *In: SESAR Innovation Days. Isdefe*, Spain.

Meloni, S., Arenas, A., Gómez, S., Borge-Holthoefer, J., Moreno, Y. (2012). "Modeling Epidemic Spreading in Complex Networks: Concurrency and Traffic." *In: Handbook of Optimization in Complex Networks*, Springer US, 435-462.

Mueller, E., Chatterji, G. (2009). "Analysis of Aircraft Arrival and Departure Delay Characteristics." *Aiaa Journal*, 1-14.

Nakata, Y., Röst, G. (2015). "Global analysis for spread of infectious diseases via transportation networks." *Journal of Mathematical Biology*, 70(6), 1411-1456.

O'Kelly M.E. (2015). "Network Hub Structure and Resilience." *Networks & Spatial Economics*, 15(2), 235-251.

Prats, X., Hansen, M. (2011). "Green delay programs: absorbing ATFM delay by flying at minimum fuel speed." *Proceedings of the 9th USA/Europe air traffic management research and development seminar*, Berlin, Germany.

Pyrgiotis, N., Malone, K.M., Odoni, A. (2013). "Modelling delay propagation within an airport network." *Transportation Research Part C: Emerging Technologies*, 27, 60-75.

Sun, Y., Liu, C., Zhang, C.X., Zhang, Z.K. (2014). "Epidemic spreading on weighted complex Networks." *Physics Letters A*, 378(7–8), 635-640.

Takeichi, N., Ishihara, J., Sato, M. (2015). "Nominal Flight Time Optimization for Minimum Delay and Fuel Consumption of Arrival Traffic." *AIAA Modeling and Simulation Technologies Conference*, Aiaa, Journal, 1-12.

Wu, W.W., Wu, C.L. (2018). "Enhanced Delay Propagation Tree Model with Bayesian Network for Modelling Flight Delay Propagation." *Transportation Planning and Technology*, 41(3), 1-17.

Yang, X.H., Wang, B., Chen, S.Y., Wang, W.L. (2012) "Epidemic dynamics behavior in some bus transport networks." *Physica A Statistical Mechanics & Its Applications*, 391(3), 917–924.

Zámková, M., Prokop, M. (2015). "The Evaluation of Factors Influencing Flights Delay at Czech International Airports." *Acta Universitatis Agriculturae Et Silviculturae Mendelianae Brunensis*, 63(6), 2187-2196.

Zanin, M., Sun, X., Wandelt, S. (2018) "Studying the Topology of Transportation Systems through Complex Networks: Handle with Care." Journal of Advanced Transportation